RESEARCH OF FOREST CLASSIFICATION BASED ON REMOTE SENSING IMAGE

Wang Erli [1,2*], Liu Xiaofang[1,2] & Wan Xin[1]
[1] School of Computer Science, Sichuan University of Science & Engineering, Zigong, China
2 Sichuan Provincial Academician（Expert）Workstation-Integrated Perception and Application of Eco-Environment in River Basins, Zigong, China

ABSTRACT
The forest plays an important role in regulating climate and improving ecological carrying capacity. In view of heterogeneous mixed young afforestation, the object-based classification on rules method is used to identify the types of planted forest, combined with spectrum, texture and shape characteristics information. ESP tool was applied to obtain the best segmentation scale and the rule set was built for the classification. The overall accuracy for classifying species was around 58%. The class-specific producer's accuracies ranged between 38% and 82% and the user's accuracies was between 33% and 96%. Compared with MLC which simply relied on the spectral information (overall accuracy 43%, kappa 0.33), the method achieved much more improvement in overall accuracy of 15 points and increased kappa coefficient to 0.52.

Keywords: *Tree species classification, Remote sensing, Object-based classification on rules method, Maximum likelihood classification*

1. INTRODUCTION
Forest is the natural resource that human live on. It plays an irreplaceably important role in supporting human social life and in sustainable development [1-2]. The distribution of forest species is the basics of operation and management of forest resources. Hence, spatially detailed tree species information is of high importance [3-4]. It is difficult to acquire detailed tree species information over large areas by traditional forest inventories. The use of remote sensing technology becomes an important mean of forest investigation at this stage [5-9]. Considering the less spatial and texture information, low and medium resolution remote sensing images could not meet the requirements of tree species classification at crown scale [10]. Data with high spatial resolution are applied to classify forests with high tree species diversity, which has proven to be the most reliable and promising technological means. Object-based image analysis approaches have also been widely used in extracting forest tree species types with its unique advantages in high spatial resolution [11-12]. However, many approaches focused on the classification of natural forest, the vegetation information of urban forestland or the extraction of single forestland type, whereas the applicability of planted forest with complicated distribution and low age is needed further discussion. This study aims at extracting young plantation tree species using spatial and spectral information provided by the Pleiades sensor applying object-based classification with rules method, so as to provide scientific basis for the formulation of relevant principles, policies and long-term planning and forest management decision.

2. MATERIALS AND THE METHODS

2.1 Study Site and Remote Sensing Images
The study site is located in Caijia River Basin, western-north of Beijing City. The annual rainfall is between 274 and 747 mm reaching a maximum amount in summer. The basin was afforested with an area of 2333.3 ha from 2012 to 2014 in the Beijing Million Acres of Afforestation Project. It is dominated by Masson pines (*Pinus massoniana Lamb.*), poplar (*Populus tremula.*), elm (*Ulmus pumila.*), Chinese pagoda tree (*Sophora japonica Linn.*), willow (*Salix matsudana Koidz.*), white wax (*Fraxinus chinensis Roxb.*) and etc. Ground is covered with Chinese Violet (*Viola philippcia Cav.*), Calliopsis (*Coreopsis tinctoria.*), dandelion (*Taraxacum officinaleWigg.*), marigold (*Tagetes erecta L.*) and *etc*, creating a large-scale ecological agriculture landscape.
The Pleiades image was recorded under cloudless conditions over the site on 27 June 2014. The leaves of all tree species are fully developed at this time of the year, providing a good condition for species classification. The high spatial resolution data has 4 spectral bands Blue (0.43-0.55um), Green (0.49-0.61um), Red (0.60-0.72um), and Near Infrared (0.75-0.95um). At nadir the ground resolution is 0.5m for the panchromatic band (0.48-0.83um) and 2m for the multispectral bands. According to the supplied calibration coefficients and spectral wavelength information, radiation correction and atmospheric correction (FLAASH model) are finished in ENVI (5.0). The multispectral bands are pan-sharpened with the panchromatic band through a smoothing filter-based intensity modulation [13] method to produce a multispectral image at 0.5m spatial resolution.

A 2000×2000 pixels sized region is clipped from the image as a tropical area to study, including artificial structure, roads, water, shadow, masson pines , poplar , elm, Chinese pagoda tree, willow, white wax and etc. Object-based segmentation and classification work are finished in eCognition (8.7) software. A pixel-based classification method called Maximum Likelihood Classification (MLC) is carried out in ENVI. In consideration of a consistent growth in afforestation, only typical trees that can represent species are measured in field investigations. Crown, diameter at breast height, tree height, strain space and GPS information are recorded, which laying a good foundation for the accuracy evaluation.

2.2 Images Segmentation

Multi-resolution segmentation in eCognition is a bottom-up region-merging. There are three factors that need to be determined in the process of segmentation: band weight, shape factor and segmentation scale [8, 14]. Band weight indicates the importance of the band contribution in segmentation. Shape factor can be decomposed into compactness and smoothness to describe the heterogeneity of the object. Compactness or smoothness is ranged from 0 to 1, and the sum of the two factors is 1. Segmentation scale fundamentally determines the size of the image object, and has become the most important factor in the process of segmentation. Based on the research of Woodcock[11] and Kim[15], Dragut[10] calculated the local variance (LV) by selecting the thresholds in rates of change of LV (ROC-LV) as the optimal segmentation scale of the scene and proposed a tool called estimation of scale parameter (ESP) integrating with eCognition. Due to the complexity of the image, there are multiple optimal segmentation scales calculated by ROC [10], and further study needs to be carried out in selecting the best one according to the characteristics of ground objects.

2.3 Classification of the Methods

The basic unit of image transfers from pixel to object with high homogeneity after segmentation. Different objects have different reflectance in remote sensing images. It makes separating the species by spectrum and texture information becoming possible. In the research, features are selected by concentrating on the texture, shape and spectral characteristics of the object. The texture features are mainly described by the 8 common features of Gray Level Co-occurrence Matrix (GLCM) [16], including homogeneity, contrast, angular second moment, entropy, dissimilarity, mean, standard deviation and correlation. Mean and standard deviation of the layer are used to meet the spectral feature requirements. Shape features are described by length and width. In addition, Normalized Difference Vegetation Index (NDVI) is constructed to distinguish between vegetation and no vegetation more prominently. Using the above characteristics, the rules are built to realize the extraction of image information by using object-based on rules classification (OBORC). Meanwhile, the traditional MLC method is selected as a compared approach with the object-based classification.

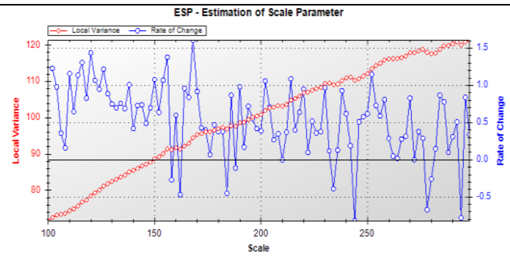
3. RESULTS AND DISCUSSION

3.1 Optimal segmentation scale

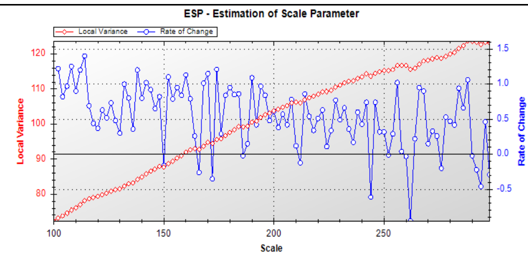
According to the differences of ground objects, both shape factor and compactness factor was tested from 0.2 to 0.8 respectively with a 0.1 step. Several groups of parameters with better segmentation results are filtered (Table1). In the consideration of near infrared band's contribution in vegetation distinction, the weight of near-infrared layer was set to 1.5 and the left layer was set to 1.0. Those parameters are entered into ESP tools to select the optimal scale parameters, and the results are shown as Figure1. The most obvious peaks were selected as indicators for optimal scale parameters and over segmentation or less segmentation points had been excluded. All the segmentation results revealed that shape of 0.3, compactness factor of 0.5 and scale of 164 were the best parameters to separate the study species, combined with visual interpretation.

Table1. Parameters with better segmentation results

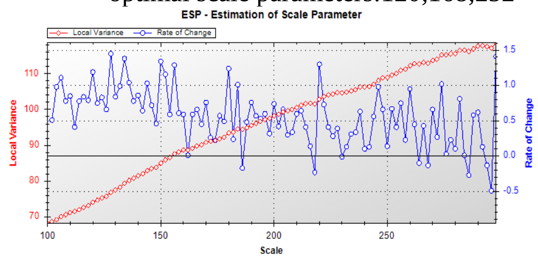
shape	compactness
0.5	0.5
0.5	0.6
0.4	0.6
0.4	0.5
0.3	0.5
0.3	0.6



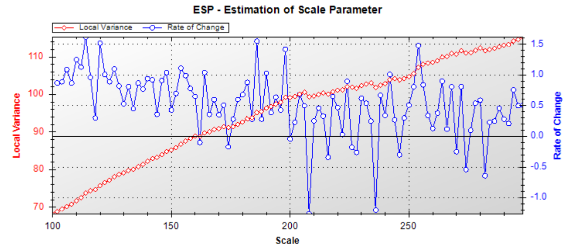
(a) shape:0.5, compactness:0.5
optimal scale parameters:120,168,252



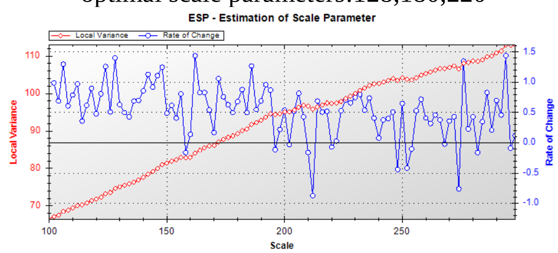
(b) shape:0.5, compactness:0.6
optimal scale parameters:114,174,256



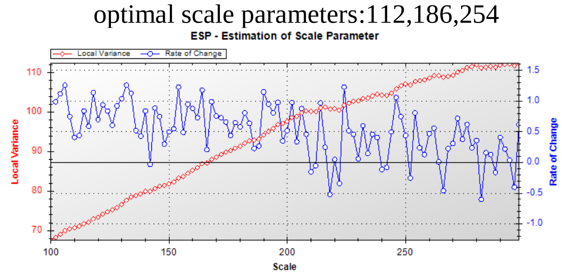
(c) shape:0.4, compactness:0.6
optimal scale parameters:128,180,220



(d) shape:0.4, compactness:0.5
optimal scale parameters:112,186,254



(e) shape:0.3, compactness:0.5
optimal scale parameters:128,164,276



(f) shape:0.3, compactness:0.6
optimal scale parameters:132,190,224

Figure1. Calculation of optimal segmentation scale

3.2 Results of Classification

Separation of objects which have significant spectral differences is easy to notice. The threshold of NDVI was chosen to classify green and non-green vegetation, and the results indicated that NDVI of 0.2 was reliable and effective. For the objects with quite similar spectrum, texture features and shape features were tested repeatedly in order to select appropriate threshold for each species. All the rules were built in eCognition software. Classification was finished by the rule set presented in Table2. Meanwhile, MLC method was realized in ENVI. The classification results are shown in Figure2.

Confusion matrix of each classifier was obtained according to the data of field survey. The matrix in Table 3 summarizes two results of the classification of 11 species. The overall accuracies were 52% and 33%, and kappa coefficients were 0.52 and 0.33. The producer's accuracies of OBORC ranged from 0.38% (elm, EM) to 82% (artificial structure, AS), and the user's accuracies from 33% (masson pines, MP) to 96% (water, WR). Producer's accuracies and user's accuracies of MLC decreased significantly. The lowest producer's accuracies of was 14% (masson pines, MP) and the highest was 69% (road, RD). For the user's accuracies, the lowest reached 0.15(masson pine, MP) and the highest reached 85% (water, WR). Comparing the results with the corresponding results of the OBORC, it is revealed that the results of the MLC approach were noticeably worse than those of the OBORC approach.

All the evidences showed that the classification of non-vegetation performed better than that of vegetation due to significant spectral differences. AS and RD were confused because of the similar spectrum, so as for the SW and WR. However, adding the length/width shape feature and NDVI to the classification, the increases in accuracy of non-vegetation results became obvious.

The spatial texture of MP differs massively from the other tree species, but it shows the lowest classification accuracy. This can be explained by the small spherical crown of MP. Few MP crowns could be covered completely a 2m multispectral pixel. It is difficult to take advantage of textural information. As for the other tree species, the larger crown contains much more spatial and spectral information which can be contributed to the precision improvements, especially in PR and WW. The similar planting density of CP and WX has also caused some texture similarities, creating confusion of between the two species.

Besides, the result of OBORC was more accurate than that of MLC due to the good quality of the segments. All the tree species were planted in lines, and the same types of species almost appeared in clustered distribution. This makes the delineation of species' boundary during segmentation process in object-based method possible, which as a result, is the main reason for the accuracy improvements.

The study area is covered by a very heterogeneous mix of young afforestation. Planting mixed with other trees species and abundant ground cover increase the species extraction difficulty from remote sensing image. Despite the achievement of a noticeable precision increase, a further improvement in classification accuracy is still necessary. Some approaches [17-18] have proved that more bands such as hyper spectral data could differ the vegetation more distinctively, and multi-temporal images [19-20] assisted in such approaches considerably. Researches in those directions should be continued.

Table2. Rule set for classification

Classified as	Rules
AS	Length/Width<3.5, NDVI<0.2, Mean_NIR>2898
RD	Length/Width>5,NDVI<0.2;Mean_NIR>3015
SW	NDVI<0, Mean_NIR<600
WR	NDVI>0, Mean_NIR<621
MP	2694<Mean_NIR<2924, 0.5＜NDVI＜0.69, 520＜Contract_B＜560, 9＜Entropy_R＜9.1
PR	3400<Mean_NIR<4100, 0.78＜NDVI＜0.89, 0.046＜Homogeneity_G＜0.050, 710＜Contract_R＜760
WW	3694<Mean_NIR<4910, 0.038<Homogeneity_G<0.046, 830<Contrast_NIR<890, 20<Dissimilarity_R_<22, 9.3<Entropy _B<9.4
CP	2850<Mean_NIR<3400, 820< Contract_R<947, 58< Deviation_NIR<72, 0.035< Homogeneity_NIR<0.04
EM	2690<Mean_NIR<2800, 0.03<Homogeneity_NIR<0.04, 850< Contrast_R<920, 22< Dissimilarity_R<24
WX	Dissimilarity_NIR<21, 3800<Mean_R<4500, 9< Entropy_B<9.3
OS	2278<Mean_NIR<2920, not above category

Note: (1) The R, G, NIR represent red band, green band, and near infrared band, respectively;
(2) artificial structure(AS), road(RD), shadow(SW), water(WR), Masson pines(MP), poplar(PR), willow(WW), Chinese pagoda(CP), elm(EM), white wax(WX), others(OS).

Figure2. Results of classification

Table3. Accuracies of classification

Classified as	OBORC		MLC	
	Prod.acc.	User's acc.	Prod.acc.	User's acc.
AS	0.82	0.70	0.53	0.67
RD	0.75	0.85	0.69	0.59
SW	0.60	0.95	0.42	0.81
WR	0.80	0.96	0.41	0.85
MP	0.39	0.33	0.14	0.15
PR	0.73	0.61	0.43	0.44
WW	0.67	0.69	0.53	0.48
CP	0.49	0.57	0.43	0.39
EM	0.38	0.52	0.26	0.38
WX	0.47	0.56	0.37	0.44
OS	0.73	0.53	0.55	0.43
Overall accuracy	0.58		0.43	
Kappa	0.52		0.33	

4. CONCLUSION

The study focused on optimal scale selecting and rule set building of single-date Pleiades data for classifying 6 tree species and 4 non-vegetation species in young stand age forest. ESP tool was applied to obtain the best segmentation scale. Combining with spectral, texture and shape feature information, objected-based classification achieved a great improvement in overall accuracy of 15 points, compared to the use of MLC which simply relied on the spectrum. Meanwhile, the kappa coefficient was increased by 0.19. Each species were more clearly separated by the OBOR method, showing a significant advantage in classifying the heterogeneous mixed young afforestation. In addition, the size of tree crown and segmentation performance affects the classification result to some degree.

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